Waiting Online versus In-Person in Outpatient Clinics: An Empirical Study on Visit Incompletion



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Background and Goal

Develop evidence-based approaches for the management and integration of telemedicine and in-person visits. Take an empirical approach to understand differences between patient's behavior online and in-person, and its implication to intraday sequencing decisions.

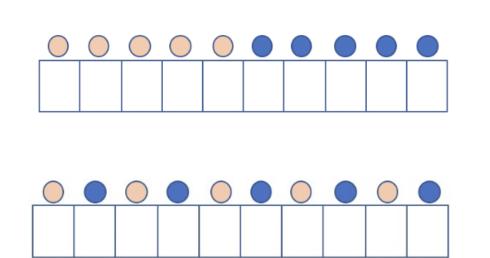
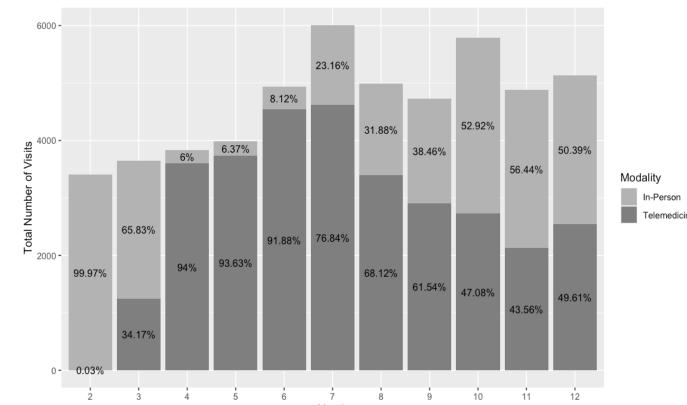


Figure 1. Intraday sequencing: block (top) vs. alternating (bottom)



Empirical Setting

Appointment data from two largest outpatient clinics of medicine department at CUIMC from Feb to Dec 2020. Average incomplete rate is 20% for both inperson and telemedicine patients.

Research Questions and Main Findings

Q: What is the impact of physician availability on visit incompletion?

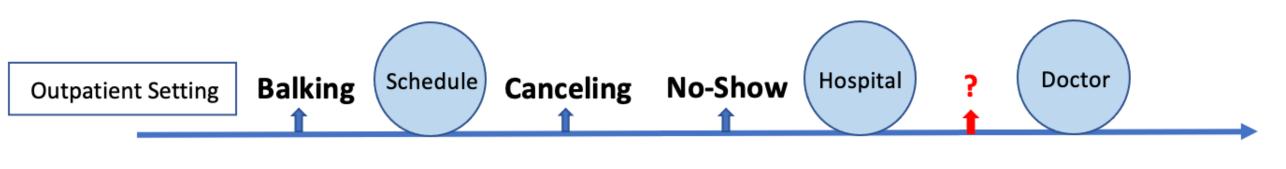


Figure 3. Patient visit process in the outpatient setting. An incomplete visit can be caused by no-show or abandonment.

A: If the doctor is *available* at the scheduled start time, telemedicine visit incomplete rate decreases by 7.4% while in-person visit incomplete rate does not change significantly. This can be translated into the abandonment rate of telemedicine patients being 9% and that of in-person patients being 0.

Estimation Strategy

Challenges: endogeneity, measurement error, and missing values Main model: multivariate probit

Incomplete_i = 1{ $\beta_1^T X_{1i}$ + $\delta Available_i$ + u_{1i} > 0} Available_i = 1{ $\beta_2^T X_{2i}$ + $\alpha_2 PreWorkProv_i$ + u_{2i} > 0} ReportTrue_i = 1{ $\beta_3^T X_{3i}$ + α_3 RelWorkClinic_i + u_{3i} > 0} $Observe_{i} = 1\{\beta_{4}^{T}X_{4i} + \alpha_{4}WorkClinic_{i} + u_{4i} > 0\}$

Observed data

 $z_{i} = \begin{cases} (X_{i}, Incomplete_{i}, Available_{i} \times ReportTrue_{i}), \text{ if } Observe_{i} = 1\\ (X_{i}, Incomplete_{i}), & \text{ if } Observe_{i} = 0 \end{cases}$ $c_i, WorkClinic_i$

$$X_i = (X_{1i}, X_{2i}, X_{3i}, X_{4i}, PreWorkProv_i, RelWorkClinic$$

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Figure 2. Total number of visits of our collaborating medicine clinics in each month of 2020, stratified by modalities.

- Trivedi 1998, Wooldridge 2010).

Counterfactual

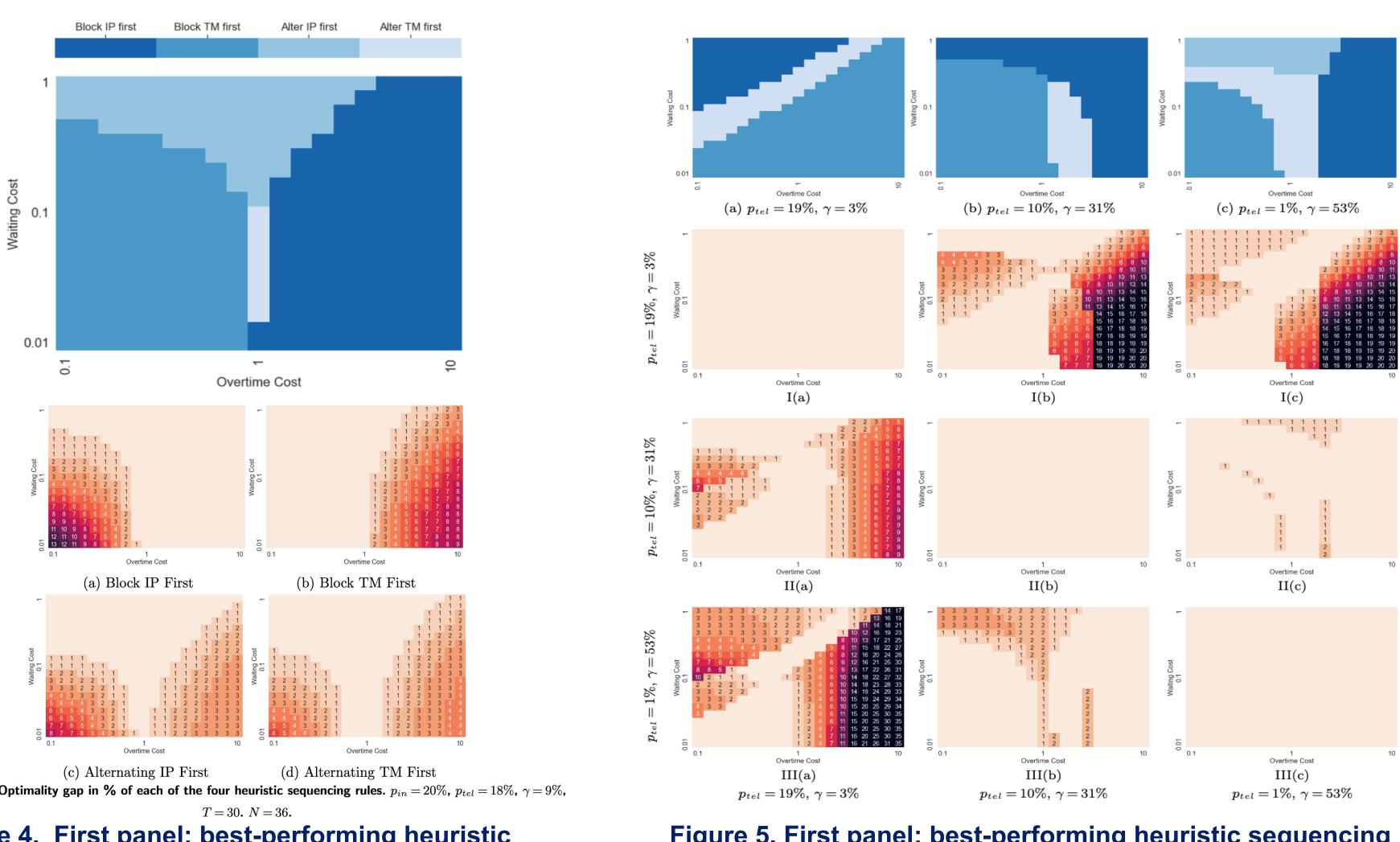


Figure 4. First panel: best-performing heuristic sequencing rules in our system dynamic. Second panel: the optimality gap when ignoring abandonment behavior.

Following Work

Mechanisms: sunk cost and waiting information

- Qualification task (base payment \$0.1) \bullet
 - Low sunk cost: 4 questions (~ 30 seconds)
 - High sunk cost: 30 questions (~ 3 minutes)
- Manipulated waiting period (6 minutes)
 - No waiting information
 - Delay announcement
 - Main task (bonus payment \$1.0)
- **Field experiment at CUIMC/NYP**

 PreWorkProvider is # of scheduled appointments within a 3-hour window prior to the focal visit of the same provider. This IV deals with endogeneity of availability. • **ReportTrue** indicates whether **Available** is correctly reported by the medical staff. The partial observability model deals with measurement error (Nguimkeu et al. 2019). Observe indicates whether Available is missing. The Heckman selection model deals with (potentially non-random) missing value bias (Wooldridge 2010). The error terms follow a multivariate normal with pairwise correlation. The full model can be estimated via Full Maximum Likelihood Estimation (FMLE) (Cameron and

> Figure 5. First panel: best-performing heuristic sequencing rules. Second panel: the optimality gap when applying the policies derived based on the wrong system dynamics

Lab experiment: willingness to wait for reward

	Low Sunk Cost	High Sunk Cost
Info: No	0.575	0.420
Info: Yes	0.435	0.431
p = 0.840	p = 0.006	p = 0.783

 Table 1. Proportion of participants that abandon
during the manipulated waiting period.





